# Geospatial modeling approaches for mapping topsoil organic carbon stock in northern part of Mongolia


Samdandorj Manaljav[1], Purevdorj Tserengunsen[2]

[1]University of Szeged, Department of Physical Geography and Geoinformatics, Szeged, Hungary
(samdandorj.tes@gmail.com)
[2]Institute of Geography and Geoecology, Mongolian Academy of Sciences, Ulaanbaatar, Mongolia
(pvvjee.pvvjgee@yahoo.com)

# Introduction and aims



- SOC is major component of the terrestrial carbon (C) pool [1; 2].
- Small change in SOC stocks can considerably increase atmospheric $CO_2$ concentrations [3; 4].
- High quality maps of SOC not only provide guidance for soil management practices but also enable more accurate estimations of C stocks [5].
- Mongolia is one of least researched areas for mapping SOC stock.
- The objectives of this study were (I) to estimate the spatial distribution of topsoil organic carbon stock in Tarialan (northern Mongolia) via Regression Kriging (RK), Geographically Weighted Regression (GWR) and Geographically Weighted Regression Kriging (GWRK) and (II) to compare the performance of these approaches.



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# Study area



Tarialan soum (sub-province) is located in the Khuvsgul province, northern Mongolia (Fig. 1). It covers an area about of 3407.3 km$^2$. The altitude of the study area ranges from 936-2052 m above sea level. The MAT is between -4 and -2°C and the MAP ranges from 250-400 mm. Due to complex topography, the main soils in the area are *Umbrisols, Leptic Chernozems, Mollic Leptosols, Kastanozems and Gelic Histosols* [6].

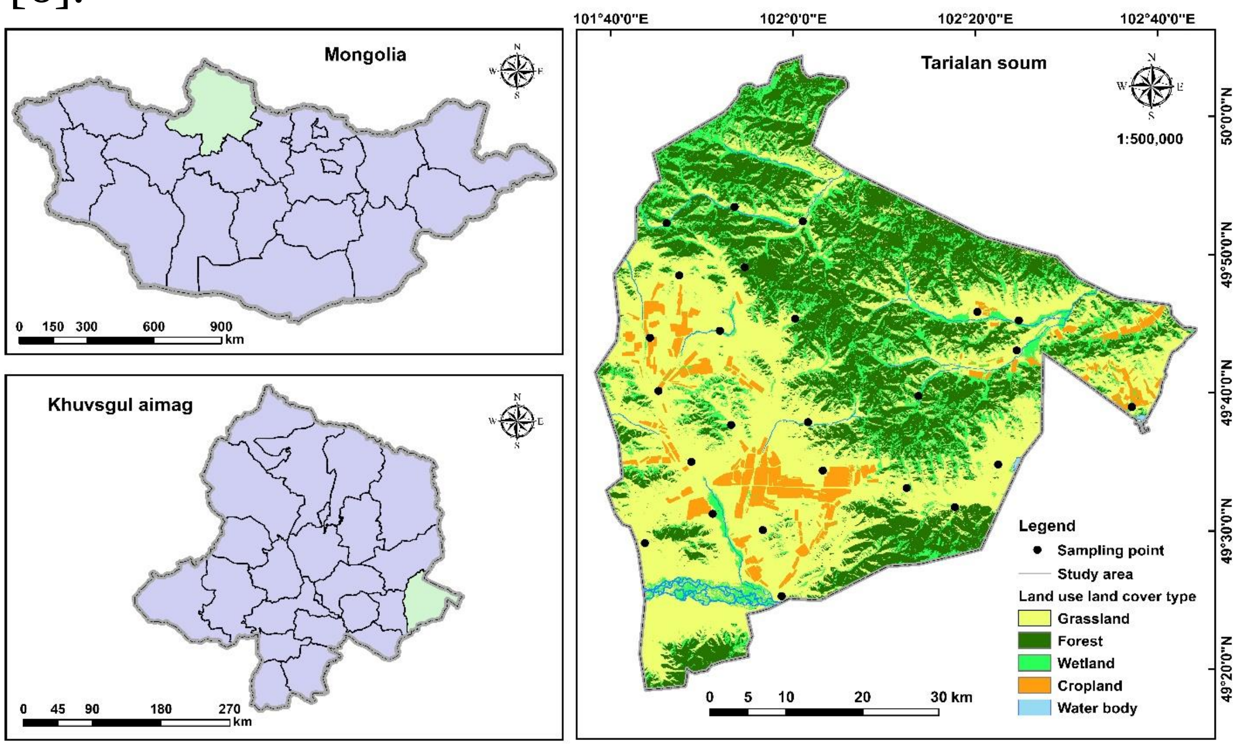


Fig 1. Location of study area and soil sampling sites.



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# Soil sampling and analysis



- The soil survey was conducted in July of 2018 and a total of 25 topsoil (0-30 cm depth) samples were taken from the entire study area based on the random sampling.
- The soil samples were air-dried and passed through a 2 mm sieve.
- Gravels (>2 mm) were sorted out and weighted.
- 95 $cm^3$ of undisturbed soil cores at 2 depths of 10 cm and 20 cm were collected from each sampling sites to measure bulk density.
- Soil organic carbon content was measured using dichromate oxidation method [7].



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# Environmental covariates



- Environmental covariates including terrain factors (elevation, slope, aspect), spectral indices (normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), soil adjusted vegetation index (SAVI)), and land surface temperature (LST) were used to predict SOC stock (kg $m^{-2}$).
- Two scenes of Landsat 8 OLI/TIRS images (Path 135/Row 25, 26) acquired in July 2017 were used to estimate spectral indices and LST. The slope gradient and aspect were generated from the ASTER GDEM v2 using ArcGIS 10.2 (Esri Inc., USA).
- All covariate layers were clipped by region of interest and projected to UTM Zone 48N.



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# Modeling approaches



We used GWR, GWRK, and RK approaches for mapping topsoil organic carbon stock.

- The Geographically Weighted Regression (GWR) considers relationships between target variable and predictors at different locations [8; 9].
- Residuals from the GWR were interpolated by ordinary kriging then the kriged residual map was added to the regression predicted map to obtain Geographically Weighted Regression Kriging (GWRK) map.
- Regression Kriging (RK) is a hybrid method that combines regression model with simple or ordinary kriging of the regression residuals [10; 11] where the residuals and drifts are fitted separately and then results were summed to obtain the final regression kriging map.

Also, performances of these models were evaluated by the mean error (ME), the root mean squared errors (RMSE) and coefficient of determination ($R^2$).



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# Results



Table 1. Comparison of the performances of GWRK, GWR, RK approaches used in this study (n=25).

| | GWRK | GWR | RK |
|---|---|---|---|
| RMSE (kg $m^{-2}$) | 1.38 | 1.48 | **0.69** |
| ME (kg $m^{-2}$) | 0.28 | -0.22 | **0.17** |
| $R^2$ | 0.76 | 0.72 | **0.94** |
| Adj $R^2$ | 0.75 | 0.71 | **0.93** |
| r | 0.87 | 0.85 | **0.97** |

Validation results indicated that regression kriging had the minimum prediction errors and GWRK models (Table 1).

Table 2. Summary statistics of the estimated SOC stock (kg $m^{-2}$) using GWRK, GWR and RK approach.

| | GWRK | GWR | RK |
|---|---|---|---|
| Max (kg $m^{-2}$) | 16.26 | 15.24 | 15.83 |
| Mean (kg $m^{-2}$) | **4.99** | **3.86** | **3.93** |
| Min (kg $m^{-2}$) | 0.28 | 0.72 | 0.16 |
| StDev (kg $m^{-2}$) | 1.95 | 2.10 | 2.11 |

Table 3. Estimated average SOC stock (kg $m^{-2}$) using GWRK, GWR and RK approach for the main land use, land cover (LULC) types.

| LULC types | Area | | GWRK | GWR | RK |
|---|---|---|---|---|---|
| | ($km^2$) | % | | (kg $m^{-2}$) | |
| Grassland | 1599.03 | 46.93 | 4.01 | 3.43 | 4.19 |
| Forest | 1068.44 | 31.35 | 4.72 | 4.25 | 3.57 |
| Wetland | 551.51 | 16.18 | **6.47** | **6.08** | **6.44** |
| Cropland | 185.32 | 5.43 | **1.63** | **1.48** | **1.80** |
| Water body | 2.96 | 0.08 | 0.00 | 0.00 | 0.00 |

Among the land use types, the highest average SOC stock was stored in wetland, followed by forest, grassland, and cropland according to the GWRK, GWR and RK approaches, respectively (Table 3).

For GWRK estimated average SOC stock of 4.99 kg $m^{-2}$ was substantially higher than those that are obtained by GWR and RK (Table 2).



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# Spatial distribution of topsoil SOC stock

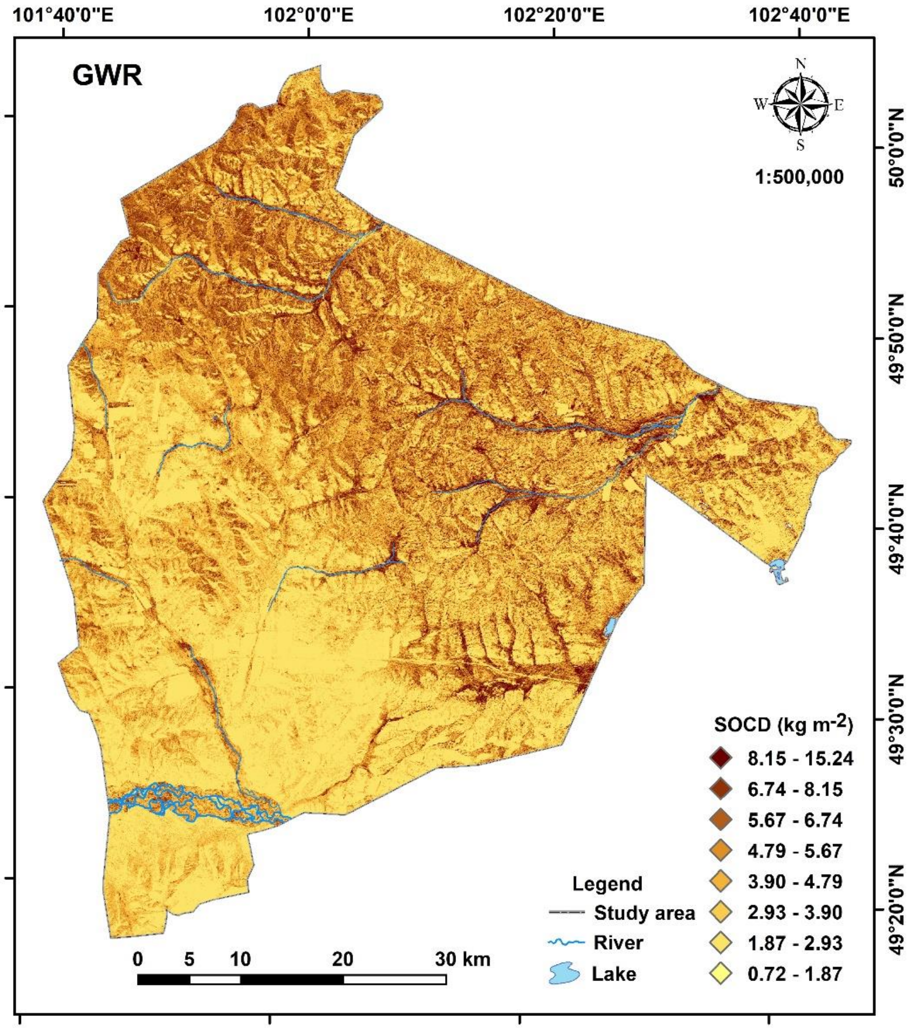


Fig 2. Spatial distribution of estimated SOC density (SOCD) or stock for the 0-30 cm depth via Geographically Weighted Regression (GWR).

# Spatial distribution of topsoil SOC stock

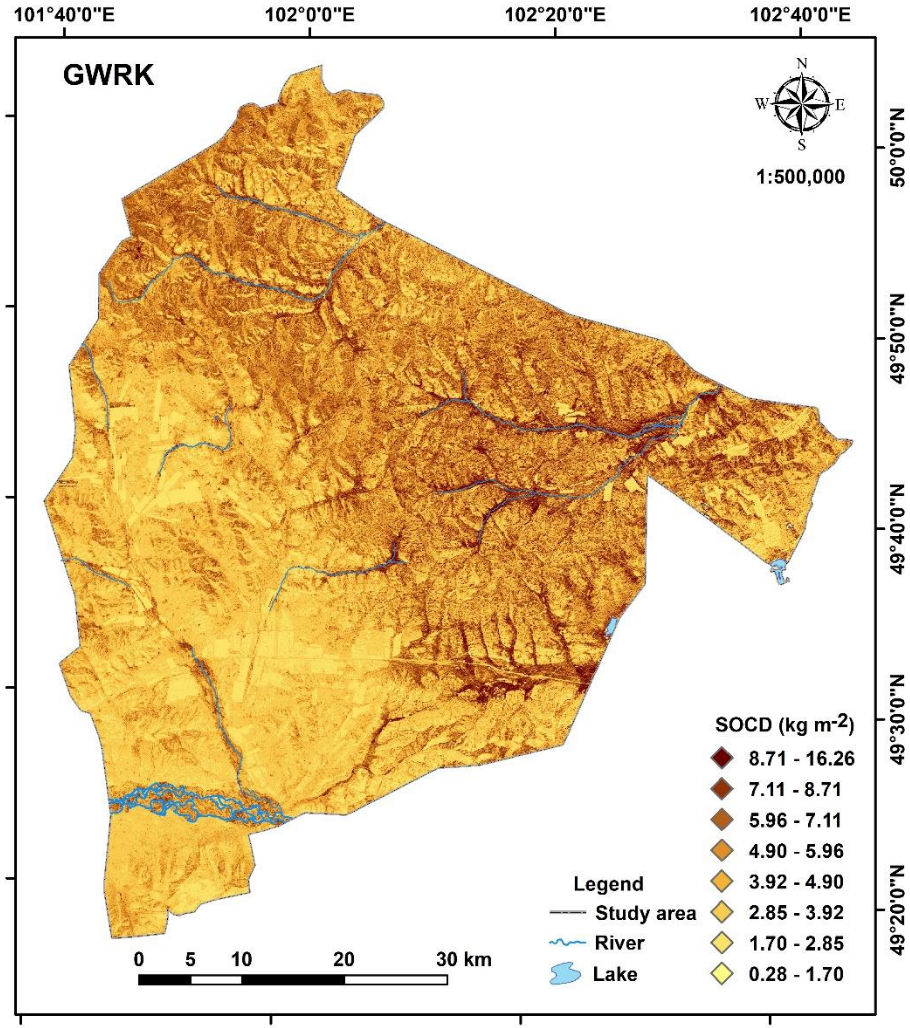


Fig 3. Spatial distribution of estimated SOC density (SOCD) or stock for the 0-30 cm depth via Geographically Weighted Regression Kriging (GWRK).

# Spatial distribution of topsoil SOC stock

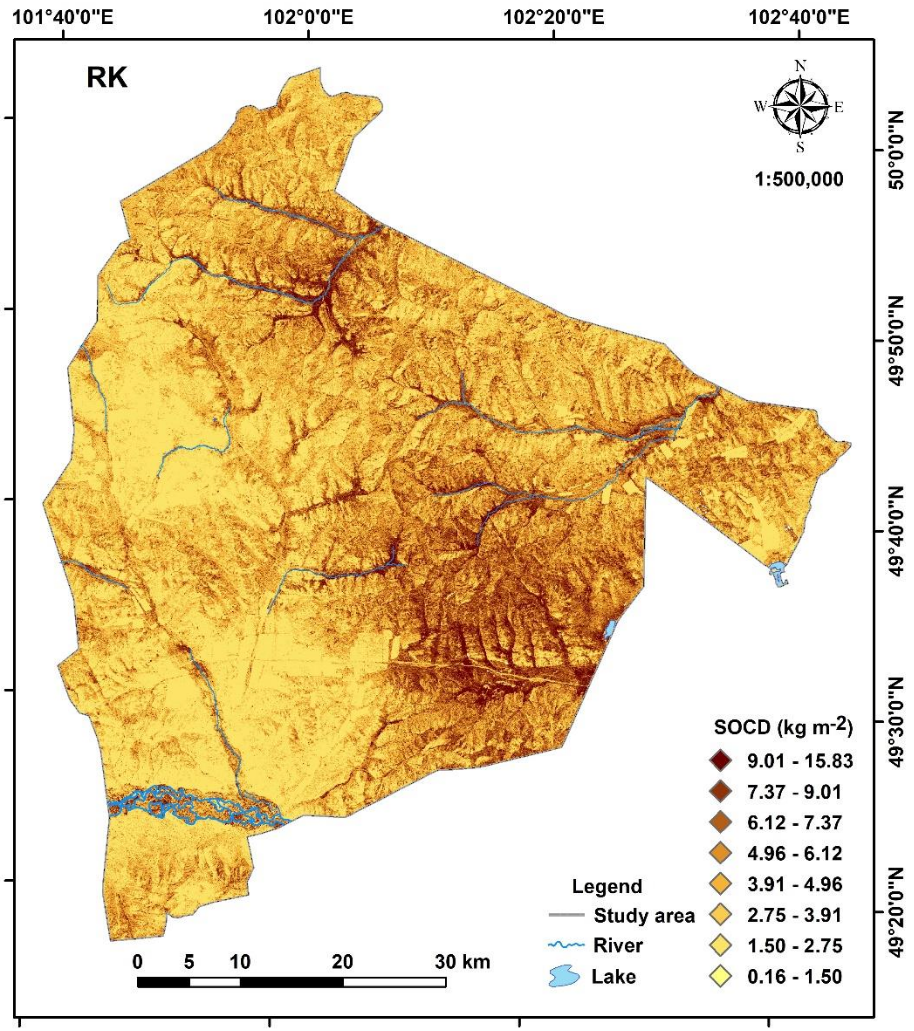


Fig 4. Spatial distribution of estimated SOC density (SOCD) or stock for the 0-30 cm depth via Regression Kriging (RK).



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# Conclusions



- The estimated SOC stock was highest in wetland, after that forest and grassland, eastern and northern parts of the area, while lowest in cropland, majority of which mainly located in the central parts of Tarialan.
- For GWR and GWRK, the estimated average SOC stocks were 3.86 kg $m^{-2}$ and 4.99 kg $m^{-2}$, independently; for RK the estimated average SOC stock was 3.93 kg $m^{-2}$.
- The two modeling approaches for mapping SOC stock, GWR and GWRK, provided quite similar (model performances of GWRK were slightly better than those of the GWR) validation results.
- RK approach showed more accurate results than GWRK and GWR methods for estimating the spatial distribution of SOC stock on a local scale.



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**Thank you very much for your attention**

If you have questions or feedback do not hesitate to contact: samdandorj.tes@gmail.com

Main results for this presentation come from M, Samdandorj, and Purevdorj Ts. 2019. Proceedings of the Mongolian Academy of Sciences. https://doi.org/10.5564/pmas.v59i2.1215.



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